THE INFLUENCE OF ADVERSE WEATHER CONDITIONS ON THE PROBABILITY OF CONGESTION ON DUTCH MOTORWAYS

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ABSTRACT

Weather conditions are widely acknowledged to contribute to the occurrence of congestion on motorway traffic by influencing both traffic supply and traffic demand. However, to the best of our knowledge this is the first paper that explicitly integrates supply and demand effects in predicting the influence of adverse weather conditions on congestion. Traffic demand is examined by conducting a stated adaptation experiment, in which changes in travel choices are observed under adverse weather scenarios. Based on these choices, a Panel Mixed Logit model is estimated. Supply effects are taking into account by examining the influence of precipitation on motorway capacity. Based on the Product Limit Method, capacity distribution functions are estimated for dry weather, light rain and heavy rain. The results show that rainfall leads to a significant increase in the probability of traffic breakdown at bottleneck locations. Remarkably it is predicted that probability of a breakdown is higher in light rain (86.7%) than in heavy rain (77,4%) conditions, which is the result of the increased traffic demand in light rain conditions. Based on the results presented in this paper, it is recommended to always incorporate both supply and demand effects in the predictions of motorway breakdown probabilities due to adverse weather conditions.

INTRODUCTION

Congestion on motorways annually leads to serious economic damage. In the Netherlands alone, 68 million vehicle hours were lost due to congestion between May 2010 and April 2011 (*1*). Weather is widely acknowledged to contribute to the occurrence of congestion in two different ways. Firstly, weather conditions can influence the traffic supply through a temporal reduction of capacity resulting from drivers reducing their speed and allowing greater time headways. A well-known piece of literature into the effect of weather on traffic flow is presented in the Highway Capacity Manual (*2*). The manual suggests capacity reduces by between 0% and 15% as a result of precipitation. Motorway capacity reduction is traditionally regarded as a deterministic phenomenon, but numerous researchers (*3-7*) have shown that the maximum capacity of a motorway varies even when the external factors are constant. This results from unpredictable behavior of drivers on the microscopic level.

Secondly, weather conditions also influence motorway traffic demand, however, this has received much less attention *(8)*. In their literature review, Böcker et al. show that many studies have found different effects of precipitation, temperature and wind on traffic demand. Call (*8*), amongst others, reported considerable reductions in trip-making with snowfall. Car traffic reductions are also reported as a consequence of rainfall, for example by Al Hassan and Barker (*9*) in Scotland. Where most studies show negative percepitation effects on trip generation, a Dutch study (*10*) found a positive relationship between precipitation and car and public transport usage. This is the result of the large number of cyclists in the Netherlands, of which a part switches to motorized transport modes in response to precipitation.

Surprisingly though, a study that combined the effects of changes in motorway capacity and motorway traffic demand to examine the effect of weather could not be found in the literature. The aim of this paper is therefore to contribute to the literature by developing and applying a method that includes both supply and demand effects of adverse weather conditions on the probability of traffic breakdown on Dutch motorways. To estimate demand effects, a stated adaptation experiment is conducted, in which car drivers choose among a range of travel alternatives depending on the presented weather conditions. Based on the observed choices, a Panel Mixed Logit model is estimated of which the results are presented and interpreted in this paper. With respect to the supply side, the focus is on the influence of precipitation on motorway capacity. This is estimated using capacity distribution functions based on the Product Limit Method. In order to arrive at a sufficient number of observations that include congestion, the analysis is limited to the morning peak period (between 6:00 and 10:00 am). Still, due to data limitations, breakdown functions could only be estimated for dry weather, light rain and heavy rain, and not for snowfall. As will be explained later, a generic model based on a cumulative normal distribution is developed that allows predicting breakdown probabilities for any given traffic demand and capacity.

METHODOLOGY

The relation between motorway traffic demand and motorway capacity

In this section, the relation between motorway morning peak traffic demand and motorway capacity is made explicit to explore the possibility of linking both factors later in the analysis. For the capacity analysis, a stochastic approach for capacity is used based on the following definition of capacity: *"the rate of flow along a uniform freeway segment corresponding to the expected probability of breakdown deemed acceptable under prevailing traffic and roadway conditions in a specific direction*" (*5*). Applying the concept of stochasticity to the motorway capacity leads to a probability density function that provides the probability of breakdown given a certain traffic flow, for which an example is shown in Figure 1.

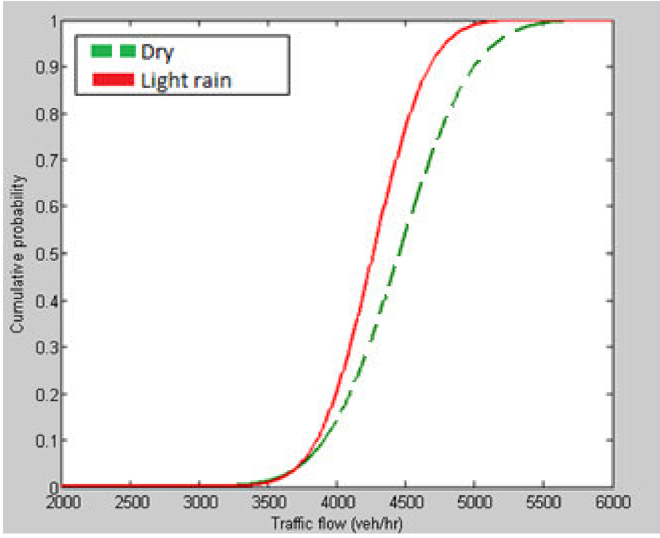

Figure 1 - Breakdown probability at motorway A4 in dry and light rain conditions

The breakdown probability refers to the likelihood of the formation of congestion for a range of traffic flow values and is defined in more detail later on in this paper. Figure 1 shows the capacity distribution function at motorway A4 in 2007 in dry weather conditions (right line) and in light rain weather conditions (left line). Comparing the breakdown probability for a given traffic flow makes clear that the probability of breakdown is higher for light rain than for dry weather. In other words, the road capacity is lower for light rain than for dry weather. Traffic flow is largely determined by motorway travel demand, hence if traffic demand increases, traffic flow increases, which in turn increases breakdown probability. This makes clear that both motorway capacity and motorway traffic demand both influence the probability of breakdown.

Capacity Analysis

Choice capacity estimation method

The Product Limit Method (PLM) (*11*) with adaptations as described in Brilon et al. (*3*), is used in the capacity analysis to arrive at probability breakdown functions. This method considers traffic flow observations upstream of a bottleneck location. Measurement upstream of a bottleneck location takes into account that the free flow capacity in uncongested traffic flows differs from the discharge capacity in congested conditions, which is the result of the so-called capacity drop phenomenon (*12-14*). Consideration of only pre-breakdown traffic flows for capacity estimation is a major difference to other PLM implementations, which also consider discharge traffic flow observations (*6; 15*).

Bottleneck location detection

The capacity estimation method relies on the occurrence of multiple breakdown observations to arrive at a reliable capacity distribution function based on a large dataset. Therefore, only static bottleneck locations with many congested morning peaks during the year are analyzed in this study. The bottleneck locations are identified by analyzing traffic data from double-induction loops present at the Dutch motorway network, which is known as the MONICA system (Dutch MONItoring Casco). For each minute data is stored regarding the average speeds (km/h), flows (veh/min) and possible lane closure for all the motorways included in the MONICA system. Data from the years 2007, 2008 and 2009 are inspected of various Dutch motorways (A2, A4, A6, A9, A15, A16, A20, A27, A50, A58 & A59).

The following three criteria need to be met for a static bottleneck location to become suitable for analysis. First, the induction loops at and around the bottleneck location should work properly. Second, congestion at the bottleneck location should not be initialized by spillback from a bottleneck downstream. Third, the bottleneck may not consist of a variable number of lanes over the day (for example peak hour lanes). In total fourteen bottleneck locations met all three requirements and were selected for the capacity analysis.

Categorization of the traffic flow observations

Observation intervals of five minutes are used, since this is considered a good compromise between reducing random fluctuations in the traffic flow and accuracy in the average intensity values (see (*3*)). Only observations within the morning peak period (6am-10am) are included in the analysis. In addition, observations of weekend days and vacation periods are excluded. Each of the remaining five-minute traffic flow observations is categorized as either a Breakdown (B), Free-flow (F) or Congestion (C) category:

B: Traffic volume is as a realization of the capacity due to the fact that observed flow in this interval is uncongested, but causes a breakdown in the following interval i + 1. Here, an average speed of 60 km/h is the applied as congestion threshold (*16*). An extra requirement for this observation is that during the preceding 6 observations (30 minutes) the average speeds were higher than 60 km/h. This is added to ensure uncongested flow before the occurrence of breakdown.

F: The traffic flow is uncongested in interval i and in interval i + 1. The information obtained from this observation shows that the actual capacity in interval i may be greater than the volume q_i that is observed. This censored data is valuable for a correct quantification of the breakdown probability.

C: The traffic flow is congested in interval i and in interval i – 1, thus the average speed in both intervals is lower than the threshold value. Since the traffic volume in interval i – 1 is also congested, the observation does not provide information about the free flow capacity and is therefore excluded from the free flow capacity analysis.

After the observations are binned by category, rain data is added to the observations. These data are collected from a data feed of the Royal Netherlands Meteorological Institute, which provides data for a grid pattern of 1 km by 1 km on a one-minute basis. The rain detection and intensity estimation is performed via advanced satellite images and has realized excellent accuracy during the latest years. The one-minute rain intensity data is averaged to five-minute intervals and these intervals are mapped onto the road network with latitudinal and longitudinal coordinates (*16*).

Capacity distribution function estimation

The classified and filtered traffic observation intervals possess information regarding the average intensity and the average speed during that interval. With the information regarding the average speed, average intensity and the category of each observation interval, it is possible to estimate a distribution function for the free flow capacity using the Product Limit Method (PLM) by Kaplan and Meier (*11*). This leads to a free flow capacity distribution function of the bottleneck, estimated using the function:

$$F_c(q) = 1 - \prod_{i:qi \leq q} \frac{k_i - d_i}{k_i}; i \in \{B\} \tag{1}$$

Where:

$F_c(q)$ = capacity distribution function
q = traffic volume (veh/h)
q_i = traffic volume in interval i (veh/h)
k_i = number of intervals with a traffic volume of $q \geq qi$
d_i = number of breakdowns at a volume of qi
$\{B\}$ = set of breakdown intervals (intervals with classification B)

Eq. 1 gives a representation of a survival function, in which traffic flow is deemed to 'fail' upon the onset of congestion. For more details, see (*3*). The calculation is made for each breakdown interval observation. Each observed breakdown is normally used as one q_i-value, which leads to d_i always being equal to 1. The factor k_i is based on all observations (thus B- and F-observations) with a traffic volume (q) that is higher than the traffic volume at the breakdown observation (q_i). The points at the capacity distribution are thus B-observations, but in order to arrive at the probability of that certain point the F-observations are also included into the estimation.

Stated adaptation experiment

In this section, the stated adaptation experiment is described that was conducted to estimate the extent of traffic demand change due to adverse weather conditions. In this experiment, hypothetical weather situations are presented to respondents and for each situation they are requested to make a choice between the following six travel alternatives:

1. Travel by car on the motorway in the morning peak
2. Travel by car, but avoiding the morning peak (before 06:00 or after 10:00am)
3. Travel by car, but avoiding the motorway
4. Travel by bicycle
5. Travel by public transport
6. Decide not to make the trip

In the following, first the construction of the weather conditions is discussed. This is followed by discussing how trip purpose was included. Then, the data gathering procedure is described. Finally, attention is given to the model estimation procedure.

Selection of attributes

A first attribute that described the weather conditions is *precipitation*, which reflects the current precipitation at the moment when the decision about a trip in the morning is made. This attribute consists of five levels, which are *dry weather*, *light rainfall*, *very heavy rainfall*, *light snowfall* and *heavy snowfall*. Pictures are included for each of the precipitation levels in order to make the terms light and heavy more tangible. This is done in order to mitigate effects due to different perceptions of precipitation conditions among the respondents.

The second attribute is the *weather alarm* that is sometimes issued by the Royal Netherlands Meteorological Institute in case of extreme weather conditions. A weather alarm with code red is issued at most twelve hours in advance if the probability of the occurrence of an event is at least 90%. It is only issued if the affected region is at least of 50 kilometers in length (*17*). The following alarms codes are applied in this experiment: *code red for heavy rainfall* (at least 75mm in 24 hours), *code red for snow* (at least 3cm per hour or 10cm per 6 hours) and *code red for icy roads*. The final level is the event of *no weather alarm*.

The third attribute is the *weather forecast*, which is included in the experiment as the weather forecast. Generally, forecasts provided by news broadcaster do not provide very specific information regarding the weather during the coming day. Based on this notion rather general levels have been formulated for this attribute, that is, during the day the weather conditions can: *improve*, *get worse* or *stay the same* as the current weather conditions.

Lastly, information regarding *temperature* was included. Although we did not expect significant effects of temperature on top of the already included attributes, this attribute was merely included for the sake of completeness and to avoid respondents guessing temperature levels based on the presented precipitation forms, which therefore reduces potential heterogeneity. The distinguished temperature values were *-5*, *+10* and *+25* degrees Celsius.

The selected attributes are combined using an efficient design to arrive at the weather condition descriptions. Based on a pilot study with 30 respondents, priors were estimated that were used to arrive at the design. To ensure that only logical weather combinations were constructed, several constraints were included.

In total, 20 different weather situations were constructed. To limit the number of conditions shown to each respondent, weather conditions were binned into two groups of 10 conditions. Each respondent was presented with only one of the blocks of 10 weather conditions.

Trip purpose

It is widely acknowledged that travel behavior can vary with trip purpose. Those traveling for work related purposes may have more limited possibilities to adapt their travel plans than those traveling for recreational purposes. Therefore those two categories are distinguished. The first category consists of business, commuter and educational trips, which we define as *utilitarian trips*. The second category consists of trips for visiting family or friends, grocery shopping, shopping, a day-out, going to sports etc. and is defined as *recreational trips*. For each of the presented weather conditions respondents are asked to indicate separately for utilitarian trips and for recreational trips their travel choice, provided they typically travel for this purpose in a normal workweek. Hence, this procedure allows estimating separate models for utilitarian and recreational trips.

Questionnaire and sample

The stated adaptation experiment was included in an online questionnaire and was preceded by questions about socio-demographic characteristics and questions about the normal travel behavior of the travelers regarding motorway use. The latter involved questions about: the number of utilitarian and recreational trips respondents make in the morning peak of a normal workweek, the mode that is most often used during a normal workweek for both purposes, the distance from home to work, the possibility to avoid the morning peak and the possibility to work at home.

Respondents were randomly selected from an existing panel of respondents that fill out questionnaires on a regular basis. In total 342 respondents filled out the survey completely (response rate of 22%), of which 210 respondents only provided responses for utilitarian trips, 71 only for recreational trips and 61 respondents provided responses for both trip purposes. This resulted in 2710 observations for utilitarian trips and in 1320 observations for recreational trips.

Model estimation

Effects coding is applied to code the attribute levels, with the result that the constant estimated for each alternative denotes the average utility derived from that alternative. The estimated effects for each attribute levels then denotes the extent to which utility of an alternative changes if that attribute level is present in the weather condition situation, which is expressed as deviations from the average utility. Effects coding resulted in four *current weather* indicator variables, two *weather forecast* and three *weather alarm* indicator variables. Preliminary analyses indicated that, as expected, *temperature* did not have any significant effects, and is therefore excluded from all models. The coded attributes were included in the utility function of the alternatives and were all estimated alternative specific.

It was expected that the choice for any of the alternatives largely depended on the current and therefore the favorite travel options during the morning peak hours. This favorite option formed the basis of a segmentation for which the following groups were distinguished: motorway car group, non-motorway car group, public transport group and cyclist group. These groups were also effects coded and added to the utility function of each alternative. Hence, a statistically significant effect estimated for a group indicator means that the utility this group derives from that alternative differs from the average utility across all groups.

The utility models were separately estimated for utilitarian and recreational travel behavior in Biogeme (*18*). A basic MNL model estimated for utilitarian trips, which included only the alternative specific weather condition attributes, returned a Log-Likelihood value of -3882.16 and a Rho-square value of 0.200. If the current travel option is added to the utility functions, the log-likelihood considerably increased to -2005.48 and the Rho-square becomes 0.587, confirming that as expected the current travel option plays a large role in the choices among the alternatives.

In addition, a panel mixed logit model is estimated to take the so called panel effect into account. This takes into account the likely correlation between the 10 observed choices of each respondent. More specifically, we assumed that the preferences for the alternative specific constants follow a normal distribution. Hence, a mean and a standard deviation for each alternative specific constant is estimated. This model is estimated by simulation for which error terms are drawn from a normal distribution. Taking the panel effect into account is done by drawing a single error term for all the 10 choices observed for a single individual. This procedure results in more valid t-values as these are no longer based on the number of observations but on the number of respondents. Taking this panel effect into account further improved the Log-Likelihood towards 1386.50 and leads to a very high Rho-square value of 0.714.

For the recreational trips, the basic MNL model returns Log-Likelihood values of -2085.69 and Rho-square value of 0.118. Including the current mode choice indicators increases the Log-likelihood towards -1846.74. The Panel Mixed Logit model also resulted in a significant improvement of the model (Log-Likelihood = -1348.86) and leads to a relatively high Rho-square value of 0.430.

Finally, some last notions need to made about the model estimation. First, in each model, we started with the full set of coefficients and removed step by step all non-significant coefficients to finally arrive at a set of only statistically significant parameters. Secondly, the estimates of both utilitarian and recreational trip panel mixed logit models did not change significantly when the number of draws was increased from 250 to 500 and are therefore considered to be stable. The presented models were estimated by applying 500 Halton draws.

RESULTS

Capacity analysis

In this section, capacity is regarded under different weather scenarios. The first scenario is the reference case of dry weather. Secondly, the effect of light rain on motorway capacity is investigated by only analyzing traffic flow intervals with precipitation intensities between 0.01 and 1 millimeter per hour. The third scenario is the heavy rainfall scenario, which includes all traffic flow intervals with precipitation intensities higher than 1 millimeter per hour. Unfortunately, analysis on the effect of snow on motorway capacity could not be carried due to the limited days with snow within the examined years (2007, 2008 and 2009) and the absence of location specific snowfall data.

A cumulative normal distribution function is fitted to the resulting data in order to arrive at a complete capacity distribution function. The comparison of the capacity is made based on the median value of the capacity distribution functions. The median value in a normal cumulative probability function indicates the highest probability of occurrence of the traffic flow and therefore gives a representative capacity value. The results can be found in Table 1.

Table 1 - Comparison of the median capacity values in the different scenarios

			Dry		Light rain		Heavy rain	
motorway	Location pre-bottleneck (hm)	location post-bottleneck (hm)	Median Free flow capacity (veh/h)	Median Discharge capacity (veh/h)	Free flow capacity difference (%)	Discharge capacity difference (%)	Free flow capacity difference (%)	Discharge capacity difference (%)
A4R-2007	30.0	31.0	4452	3612	-4.2%	-6.6%	-10.3%	-5.3%
A4R-2008	30.0	31.0	4426	3624	-6.3%	-5.0%	-10.8%	-7.0%
A4L-2007	23.5	21.5	4368	3816	-3.9%	-4.1%		
A12R-2007	35.5	37.1	7173	5628			-7.3%	-5.1%
A12R-2008	68.1	68.7	4690	3864	-4.1%	-6.2%		
A15L1-2008	59.5	58.1	7267	6240	-4.4%	-6.9%		
A15L2-2007	80.9	80.1	4351	3768			-9.5%	-8.3%
A15L2-2008	80.9	80.1	4117	3792			-9.9%	-8.5%
A20R1-2007	31.0	31.9	6072	5460	-5.8%	-3.7%		
A20R1-2008	31.0	31.9	5939	5484			-7.5%	-7.7%
A20R2-2009	43.0	44.9	4205	3432			-11.0%	-4.2%
A20L-2007	32.2	31.2	6060	5268			-3.8%	-6.2%
A20L-2008	32.2	31.2	6064	5292			-3.7%	-6.3%
A20L-2009	32.2	31.2	6121	5388			-6.0%	-5.8%
A27L-2007	35.4	34.7	3938	3624			-6.1%	-5.0%
A27L-2008	35.4	34.7	3931	3624	-7.7%	-5.0%		
A50R-2007	156.3	157.5	4224	3516			-11.1%	-6.1%
A50L-2007	153.5	150.9	4181	3732	-8.9%	-7.1%	-8.1%	-9.0%
				Average	-5.7%	-5.6%	-8.1%	-6.5%
				Standard deviation	1.9%	1.3%	2.6%	1.5%

Light rainfall results in an average capacity reduction of 5.7% compared to dry weather. The capacity reduction if the results from different bottleneck locations are analyzed, with the capacity reductions ranging from 3.9% to 8.9%. It is interesting to note that heavy rainfall, on average, leads to a higher capacity reduction than light rainfall for free flow capacity, which is in accordance with expectations. This is a statistically significant difference, but the difference is rather small (5.7% vs. 8.1%) considering the fact that light rain only includes observations with rain intensities less than 1mm/hour and heavy rain includes all observations equal or higher than 1 mm/hour. Compared to this difference, the difference in capacity between dry conditions and light rain is relatively large.

Observations of the capacity reductions for the same weather condition at the same location leads to the conclusion that the capacity reduction at a bottleneck location is very robust and does not change much over time. Given the small differences between the data of the same location, suggests that the large differences between observations at different locations (between -3.7% and 11.1%) are caused by infrastructural differences between the various locations. Different road surfaces at the different locations may be an important candidate factor for explaining these differences. It could be the case that the capacity reduction is smaller on motorway sections with porous asphalt. These results are in accordance with Cools, Moons and Wets (*19*) who found heterogeneity in the effect of rain on different traffic count locations and homogeneity of the rain effects on the upstream and downstream of the same location. Comparing the results obtained in the analysis with the findings from other studies leads to the conclusion that most other researchers have found capacity reductions that are within the same range as in this contribution, leading to an increased confidence concerning the results found here.

The estimated motorway travel demand model

The estimated parameters of both utilitarian and recreational trips panel mixed logit models are presented in Table 2. As discussed before, all parameters are estimated alternative specific, hence, per model the table shows five sets of parameters. The alternative 'not making a trip' served as a reference alternative and therefore has utility of zero by definition. If an ASC (alternative specific constant) or any other attribute is not listed, this means that its coefficient is not statistically significant. The presented SIGMA's are the estimated standard deviations of the normally distributed ASC.

Table 2 - Results of the estimated Panel Mixed Logit models

	Utilitarian trip analysis			**Recreational trip analysis**	
	coefficient	t-value		Coefficient	t-value
Motorway			***Motorway***		
snow alarm	-0.57	-2.63	ASC	-2.01	-7.24
icy roads alarm	-0.82	-4.05	icy roads alarm	-1.19	-5.23
light rain	2.20	6.61	light rain	1.74	5.14
light snow	-1.23	-6.63	very heavy rain	0.49	2.11
heavy snow	-2.77	-12.49	heavy snow	-2.24	-8.28
motorway car group	4.69	16.77	motorway car group	2.23	7.81
public transport group	-3.89	-4.75	SIGMA	-2.38	-9.14
SIGMA	-3.61	-12.92			
Avoid morning peak			***Avoid morning peak***		
heavy snow	-0.88	-3.68	ASC	-0.78	-5.10
SIGMA	-1.29	-6.68	worse forecast	-0.56	-3.08
			better forecast	0.61	3.55
			light rain	0.90	3.05
			heavy snow	-1.36	-5.85
			SIGMA	1.15	9.50
Avoid motorway			***Avoid motorway***		
rain alarm	0.55	2.62	ASC	-2.99	-8.03
icy roads alarm	-1.23	-3.74	icy roads alarm	-0.71	-2.92
light rain	1.35	3.33	light rain	1.08	3.42
heavy snow	-2.43	-7.93	light snow	-1.47	-4.40
non-motorway car group	3.97	16.95	heavy snow	-1.79	-6.31
public transport group	-5.82	-4.76	motorway car group	-2.48	-6.69
SIGMA	-4.30	-11.76	non-motorway car group	2.79	6.59
			SIGMA	3.78	7.86
Bicycle			***Bicycle***		
alarm3	-1.50	-4.10	ASC	-2.72	-7.33
light rain	2.24	4.22	snow alarm	-1.60	-4.06
very heavy rain	-2.31	-3.7	light rain	1.05	2.96
light snow	-1.10	-2.87	light snow	-0.72	-2.27
heavy snow	-2.84	-4.95	heavy snow	-2.07	-4.50
motorway car group	-6.99	-7.02	motorway car group	-1.78	-6.77
motorway car group *	-3.53	-3.57	motorway car group *	1.24	4.24

very heavy rainfall			very heavy rainfall		
public transport group* very heavy rainfall	2.21	3.53	SIGMA	-2.35	-11.99
SIGMA	-3.58	-7.09			
Public transport			***Public transport***		
light rain	1.13	3.05	ASC	-9.33	-4.31
heavy snow	-1.09	-3.46	SIGMA	-5.23	-5.26
motorway car group	-4.18	-8.00			
non-motorway car group	-1.66	-3.34			
public transport group	6.90	9.24			
public transport group * heavy snowfall	-1.08	-2.73			
SIGMA	3.06	9.29			
Not making a trip			***Not making a trip***		
ASC	0.00	reference	ASC	0.00	reference
Log-likelihood	-1386.50			-1348.86	
Rho-square	0.714			0.430	

In the following, the main findings are discussed starting with the utilitarian trips. The results indicate that *weather forecast* does not affect travel behavior for utilitarian trips. The *current weather* and a *weather alarm*, on the other hand, have significant effects. *Rainfall*, does not have a significant effect on trip generation as suggested by the results for the ‘avoid morning peak’ alternative. *Heavy snowfall*, on the other hand, increases the probability of not making a trip.

Furthermore, the results suggest that mode choice changes do not often occur as a result of weather conditions. There is a very small shift in the cyclists group towards car use, but this effect can be considered marginal. Route choice changes for car users are also limited. Travelers that normally use the motorway do not change their route and avoid the motorway in case of severe weather conditions. Also, changing routes is not very common for non-motorway travelers. Departure time changes (‘avoid morning peak’) only occur if there is a weather alarm, hence, the effect of weather conditions on departure time change is limited. The main decision that utilitarian travelers make is whether to stay at home or make their normal trip.

The influence of the weather conditions on recreational trips is slightly different from the utilitarian trips. Weather forecasts plays a smaller role in avoiding the morning peak. When travelers know that the weather is going to improve they tend to avoid the morning peak. Both the current weather and the weather alarm have stronger impact on travel behavior for recreational trips than for utilitarian trips. Trip generation of recreational trips is significantly influenced by adverse weather conditions. Heavy rainfall leads to relatively high probabilities of not performing a trip. Heavy snow combined with a snow or icy roads alarm even leads to probabilities of 67.4% to 80.4% of not making the trip.

Mode choice changes for recreational trips occur more than for utilitarian trips. In rainy conditions there is a significant modal shift from bicycle towards car. Route choice changes for recreational trips are similar to those for utilitarian trips. There is however a relatively high route choice change (up to 22.3%) for the non-motorway user group in case of heavy rain. Departure time changes more often in comparison to utilitarian trips. Overall, the alternative ‘avoid morning peak period’ is preferred by recreational trip travelers. A possible explanation for this is (to some extent) the more flexible nature of the recreational trips as compared to utilitarian trips.

Based on the estimated model, it can be predicted that as a result of the behavioral travel adaptation of travelers, the motorway traffic demand increases by 2.3% with light rainfall compared to dry weather, while demand decreases: by 2.3% in case of heavy rainfall; by 7.7% in case of very heavy rainfall, by 22.2% in case of light snowfall, and by 29.4% in case of heavy snowfall. Furthermore, the addition of a weather alarm reduces travel demand by 19.4% in case of heavy rain and a rain alarm, by 48.8% in case of heavy snow and a snow alarm, and by 52.4% in case of heavy snow in combination with an icy roads alarm compared to dry weather.

Effect of precipitation on breakdown probability

A generic model is developed that provides information regarding the breakdown probability of traffic on all Dutch motorways. Input necessary for predicting breakdown probability is the median capacity value and the traffic flow in the different precipitation scenarios. The difference in traffic flow relating to one standard deviation in breakdown probability is computed for all bottleneck situations and scenarios, and the average of these values is taken. This results in corresponding traffic flow changes at one standard deviation of 8.6% for dry weather, 7.0% for light rainfall and 7.4% for heavy rainfall. Due to the different standard deviations for the different rain scenarios, one function and plot is made for each of the scenarios, which can be seen in Figure 2a-c.

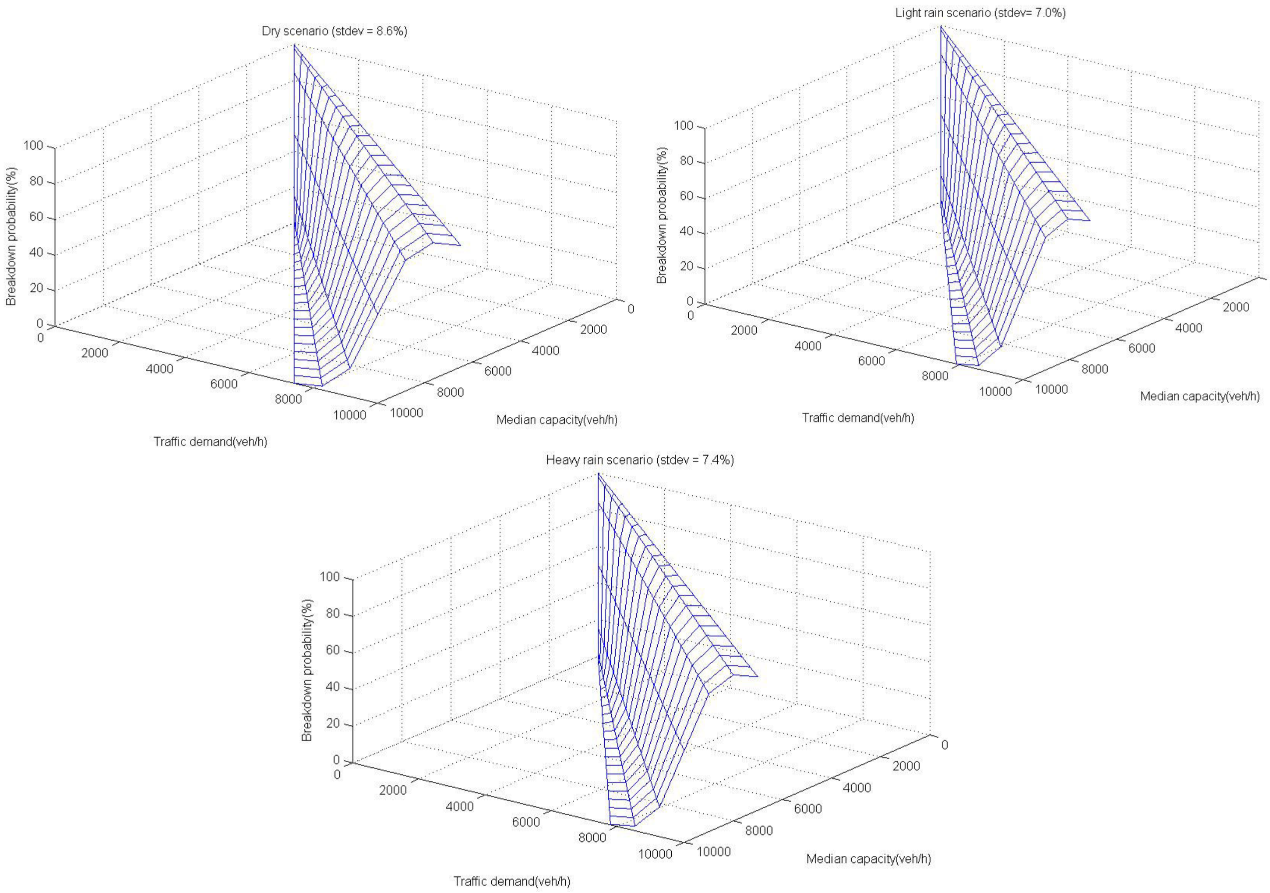

Figure 2a-c 3D-plot breakdown probability dry scenario (a), light rain scenario (b) & heavy rain scenario (c)

With the development of the three generic models, breakdown probabilities can be calculated for any given traffic demand and median capacity. When the median capacity value of a certain bottleneck and the traffic demand are known, the intersection of this point with the function leads to the breakdown probability value. The resulting breakdown probability in the dry scenario can be used as a reference value. Inserting the adjusted traffic flow (reference traffic flow with the demand change) and the reduced median capacity into the model leads to a breakdown probability for a specific scenario for a specific motorway.

The traffic flow corresponding to the median capacity is used as a reference value. If the traffic flow is equal to the median capacity, this results in a breakdown probability of 50%. The traffic demand changes of +2.3% for light rain and -2.3% result in the traffic flow values per bottleneck location in these scenarios. The median capacity values for the bottleneck locations in the different scenarios are also presented. Furthermore, the average breakdown probability increases from 50% to 86.7% in light rain conditions. This is the result of the decreased capacity and an increasing traffic demand in this scenario. The range of breakdown probabilities for the different locations is between 81.7% and 94.6%, which can be explained by the different capacity reductions for the bottleneck locations. In the heavy rain scenario the average breakdown probability is increased from 50% to 77.4%. There is a larger range in the breakdown probability for the heavy rain scenario resulting from the relatively low breakdown probability on motorway A20L and A27L. The average probability of breakdown is lower than in the light rain scenario, while the average capacity reduction in the heavy rain scenario is larger than in the light rain scenario. This is the result of the decreased traffic demand in the heavy rain scenario.

CONCLUSIONS

This paper reports on unique work that incorporates both the motorway traffic demand change and the motorway capacity reduction in the estimation of the congestion probability as a result of adverse weather conditions. A stated adaptation experiment was conducted and a Panel Mixed Logit model is estimated to predict motorway traffic demand in adverse weather conditions. To examine the influence of precipitation on motorway capacity, distribution functions were estimated for dry weather, light rain and heavy rain based on the Product Limit Method. With the development of a generic model based on a cumulative normal distribution, breakdown probabilities can be calculated for any given traffic demand and capacity.

Capacity reductions at single bottleneck locations are very robust and do not change significantly over the years. A plausible explanation is that different motorway characteristics cause these differences. The road surface at the different locations may be an important factor in the reduction of motorway capacity. Future research needs to examine the effects of different road surfaces, so the road authorities are able to choose the type of road surface at the bottleneck locations that reduces capacity the least.

The most important result of the stated adaptation experiment is that the motorway traffic demand increases by 2.3% with light rainfall and decreases by 2.3% in the heavy rainfall scenario as a result of the behavioral adaptation of travelers. The relatively small influence of rain on motorway traffic demand in the morning peak hours significantly influences the breakdown probability at the motorways. An increase in demand of only 2.3% results in an increase in breakdown probability of 11 percentage points at a specific bottleneck location.

Combining both traffic demand change and capacity reduction leads to the conclusion that rainfall leads to a significant increase in the probability of traffic breakdown at bottleneck locations. A breakdown probability of 50% in dry weather leads to an average breakdown probability of 86.7% in light rain and 77.4% in heavy rain conditions. The higher breakdown probability in light rainfall is caused by increased traffic demand, mainly caused by cyclists switching to using car.

Based on the results presented in this paper, it can be recommended that both traffic demand and motorway capacity need to be incorporated in the analysis of predicting adverse weather conditions on breakdown probabilities. Furthermore, the finding that breakdown probabilities as a result of precipitation differ at different locations, can be taken into account by road authorities in the decision to assign budgets to motorway improvement projects. Making more investments in the bottleneck locations at which rain leads to the biggest increase in breakdown probability could contribute to meeting the congestion reduction goals set by policy makers.

The results obtained regarding the demand changes in this research have three limitations. Firstly, the results are based on stated behavior instead of revealed behavior. As common for stated research, stated behavior may differ from actual behavior. Moreover, the hypothetical weather situations may be differently interpreted by respondents. Secondly, the results of the travel behavior analysis are average changes in motorway traffic demand. With the high importance of small changes in travel demand, investigating the effect of location specific rainfall on the motorway traffic demand should be considered. Thirdly, there was no data available of the number of travelers in the different travel groups (car motorway, car non-motorway, public transport and bicycle). In this contribution the importance of the groups was based on the number of respondents of the groups in the sample. More valid data regarding the distribution of the groups in the population may increase the accuracy of the traffic demand predictions.

An analysis of the effect of snow on motorway capacity could provide a valuable addition. In order to come to sufficient breakdown observations on days with snowfall, it is advised to combine the traffic data from a longer time period at the same bottleneck location than applied in this paper. The snow analysis would be more accurate if reliable location specific snowfall information could be obtained. Lastly, it might be valuable to analyze whether the filtering algorithm can cope with breakdown observations at snow conditions.

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